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# Predicting Economic Optimism and Pessimism: A Hybrid Econometric–Machine Learning Approach for Socioeconomic Forecasting

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## Abstract
This study investigates how individuals' economic outlooks are influenced by their opinions of the current economic condition and their personal traits, including demographics and socioeconomic factors. Analysis of the Rural Consumer Confidence Survey data of the Reserve Bank of India indicates that incorporating subjective perception measures enhances comprehension of the elements affecting economic outlook compared to their exclusion. The inclusion of these subjective measures in the response analysis significantly enhanced the model's capacity to elucidate the factors influencing future economic optimism. The study's results unequivocally demonstrate that the most significant predictors of future economic optimism are perceptions of overall economic conditions and anticipated employment opportunities, while the influences of perceptions regarding income, spending, and inflationary price increases are considerably weaker. The convergence of econometric and machine learning studies indicates that the study's findings are robust and consistent. This study's findings indicate that future economic optimism will be more closely associated with individuals' anticipatory macroeconomic and labour market expectations than with their present socioeconomic situation or personal attributes. This indicates that individuals' future economic optimism will be shaped by their perceptions of the economy and the signals they receive regarding the future of employment within it.

**Key Words:** Economic optimism, Subjective perceptions, Employment expectations, Logistic regression, Machine learning.

## Introduction
The positive believe about future economic situation can be expressed as economic optimism (Puri & Robinson, 2007), whereas, economic pessimism (Hey, 1984) reflects the opposite dimension of personality. Increasingly, economic optimism and pessimism affect consumer

consumption, saving, investment, and responses to macroeconomic policy (Kaida & Kaida, 2019; Mynarikova & Posta, 2023). The labor supply, credit demand, and aggregate demand can fluctuate considerably based on economic conditions, hence amplifying or mitigating business cycle characteristics (Kuhnen & Hahn, 2017; Primc et al., 2020). Contemporary macroeconomics and behavioral economics regard expectations and sentiment as active determinants of economic results, rather than mere reflections of underlying factors. Consumer confidence surveys are increasingly incorporated into forecasting models and policy evaluations as predictors of GDP, inflation, and employment. This perspective considers macroeconomic fundamentals and households' reported experiences of income security, price dynamics, and financial fragility as determinants of the economic outlook.

Increasing empirical data indicate that household optimism and pessimism regarding the macroeconomy influence consumption, labor market participation, and savings decisions, hence impacting aggregate variations (Bhandari et al., 2025; IMF, 2018). Behavioral macroeconomic models stress that the collective sentiment and perception-driven feedback mechanisms can induce economic cycles in the absence of significant fundamental alterations (Akerlof & Shiller, 2009; IMF, 2018). Concurrent studies on consumer confidence indicate that meticulously crafted emotion indicators forecast future output, unemployment, and expenditure more accurately than actual economic and financial statistics. These indicators are progressively employed as summary statistics of households' economic experiences, encapsulating risk, insecurity, and resilience that traditional macroeconomic metrics fail to adequately measure (D'Acunto et al., 2025; BIS, 2022).

In the context of imperfect information and uncertainty, households formulate economic expectations by evaluating employment opportunities, income fluctuations, expenditure pressures, credit circumstances, and pricing (D'Acunto et al., 2025; Coibion et al., 2022). Recent cross-national surveys reveal consistent discrepancies between subjective perceptions of inflation and unemployment and expert estimates or actual outcomes, suggesting that expectations are based on prominent experiences rather than statistical models (D'Acunto et al., 2025; BIS, 2022). The findings distinguish between objective socioeconomic status, measured by income, assets, or employment status, and subjective economic perceptions, such as job insecurity, the effects of inflation on real wages, and the ability to meet basic expenses. Heuristics, significant price volatility, and narratives aid families in assessing potential risks in unstable and unpredictable environments (Coibion et al., 2022; BIS, 2022). This aligns with expectation-driven and behavioral perspectives, emphasizing the impact of restricted rationality, information asymmetries, and emotional responses on economic optimism and pessimism, absent a formal structural framework (Akerlof & Shiller, 2009; Coibion et al., 2022).

***RQ1: Do subjective economic perceptions provide substantially greater explanatory power for future economic optimism than demographic and socioeconomic characteristics?***

Despite the abundance of comprehensive survey data, empirical studies on consumer confidence and expectations primarily utilize linear econometric models, including ordinary least squares, linear probability models, or fundamental logit/probit specifications, to limit non-linearities and interaction effects among the factors influencing sentiment (Kumar et al., 2017; Coibion et al., 2022). The primary objective has been explanatory inference, identifying statistically significant confidence correlates rather than enhancing out-of-sample predictive

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performance or accurately characterizing households as optimistic or pessimistic (Kumar et al., 2017; Baghestani, 2023). Numerous index construction methodologies systematically consolidate neutral or "no change" replies into balance statistics, so obscuring neutral expectations and perhaps omitting data regarding authentically uncertain or ambivalent households (European Commission, 2006; Kumar et al., 2017). The literature on machine learning applications in macro finance is expanding; yet, studies on expectations and sentiment have inadequately incorporated flexible, non-linear learning algorithms alongside conventional econometric methods. These inconsistencies indicate the necessity for empirical methods to elucidate and forecast economic optimism and pessimism, while acknowledging non-linearities in perception-based variables (Chakraborty & Chaudhuri, 2024; Baratsas et al., 2024). Limited research integrates causal style inference with high-dimensional, non-linear prediction within a singular empirical context, hence constraining interpretability and the forecasting utility for policy institutions (Baratsas et al., 2024; Baghestani, 2023). This research introduces a hybrid framework employing Binary Logistic Regression and a Radial Basis Function Neural Network (RBF NN) to assess family economic projections for one year (Baratsas et al., 2024; Baghestani, 2023). Binary Logistic Regression assesses the impact of employment, income, price, and spending pressures on optimism compared to pessimism (Kumar et al., 2017; Coibion et al., 2022). The RBF neural network identifies non-linear complex interactions among these factors to enhance predictions of optimism and pessimism (Baratsas et al., 2024; Baghestani, 2023).

***RQ2: What particular subjective perceptions exert the most significant influence on individuals' expectations regarding future economic conditions?***

A significant contribution to the research on economic expectations and consumer confidence is the explicit distinction between the functions of explanation (logistic regression) and prediction (RBF neural networks) within the same data and institutional framework. The empirical study employs the Reserve Bank of India's esteemed, policy-relevant Rural Consumer Confidence Survey (RCCS) to assess rural households' current and one-year forecasts for the overall economy, income, employment, price levels, and spending behaviors. Rural households in India exhibit cautious confidence over future income and expenditure, notwithstanding apprehensions about inflation and labor market conditions, rendering the dataset valuable for examining optimism and pessimism (Kumar et al., 2017; Indian Express, 2025). Central banks evaluate short- to medium-term sentiment to gauge policy transmission and demand robustness (New York Fed, 2025; D'Acunto et al., 2025). The study examines the contrast between optimism and pessimism regarding the general economic outlook one year in advance, categorizing neutral replies as conceptually separate and meticulously analyzing them to enhance inference and prediction for distinctly optimistic and pessimistic rural households. Therefore, this research tries to identify the determinants of economic outlook for the upcoming year, to compare the role of perceptions versus the role of Socio-economic variables, and to predict the economic outlook using machine learning. This study endeavors to examine three important questions and hypotheses:

***RQ3: Do econometric and machine learning approaches converge in identifying the primary drivers of economic optimism?***

The following section discussed the literature review in detail. Section 3 & 4 provide a comprehensive depiction of the methodology and results respectively. In section five a complete discussion was conducted on the research undertake. The last section delves into the research implications, scope of future research, and concluding remarks.

## 1. Literature Review

Macroeconomic analysis and policy formulation rely on economic expectations and consumer confidence, which transform information, beliefs, and sentiment into economic behaviour (Akerlof & Shiller, 2009; Bhandari et al., 2025). Expectations can influence consumption, investment, and business cycles even in the absence of fundamental changes; thus, a comprehensive empirical analysis of their formation, response to shocks, and modelling and forecasting is essential.

### 2.1. 1. Consumer Confidence and Economic Outlook

Contemporary and traditional studies indicate that consumer confidence and anticipatory sentiment more accurately forecast aggregate consumption and output than macroeconomic indicators (Chakraborty & Chaudhuri, 2024; Kumar et al., 2017). Confidence shocks can elicit lasting effects on consumption and business cycles, indicating that expectations influence macroeconomic dynamics more than actual outcomes (Bhandari et al., 2021; IMF, 2018). Consumer confidence indices, derived from survey inquiries into present circumstances and future expectations, frequently forecast household expenditure and private investment (Chakraborty & Chaudhuri, 2024; Kumar et al., 2017). Central banks and fiscal authorities must observe forward-looking sentiment indicators associated with recessions and recoveries (Bhandari et al., 2025; IMF, 2018).

***H1:*** *Consumer confidence has a significant positive influence on households' economic outlook, such that higher confidence levels are associated with more optimistic expectations regarding consumption, income, and overall economic performance.*

### 2.1.2. Socioeconomic Elements Influencing Outlook

The economic perspective is influenced by age, gender, education, income, occupation, and employment stability (Coibion et al., 2023; He et al., 2024). Individuals with higher income and education levels exhibit greater optimism regarding income, employment, and inflation compared to younger, less educated, and financially constrained households (Coibion et al., 2023; D'Acunto, 2025). Incorporating subjective impressions and experience-based variables into multivariate models diminishes the explanatory value of objective features (D'Acunto et al., 2025; He et al., 2024). Coibion et al. (2023) and He et al. (2024) juxtapose sociodemographic factors with perception-based variables as predictors of optimism and pessimism.

***H2:*** *Socioeconomic characteristics including income, education, age, occupation, and employment stability significantly shape individuals' economic outlook, with higher-income and better-educated households exhibiting greater economic optimism than financially constrained groups.*

### 2.1.3. Economic feelings and views

Recent research highlighted subjective perspectives of employment prospects, income dynamics, and cost-of-living pressures as key determinants impacting sentiment and expectations (Coibion et al., 2023; D'Acunto et al., 2025; Rath, 2025). Many household surveys across countries show that perceptions of inflation and unemployment differ from official figures or expert estimates, with many households sensing higher real-wage losses and poorer labor markets. It was found that perceived inflation, price salience, and major spending experiences predict pessimism and precautionary behaviour more than objective income or employment characteristics (BIS,2025; Coibion et al., 2023). These findings suggest that lived economic experiences and prominent shocks have a greater impact on expectations than aggregate indicators, resulting in lasting differences between subjective and objective economic situations (BIS, 2025; D'Acunto et al., 2025).

***H3:*** *Subjective economic feelings and perceptions (e.g., perceived inflation, employment prospects, and cost-of-living pressures) exert a stronger influence on consumers' economic outlook and precautionary behavior than objective macroeconomic indicators.*

**2.2.1. Methods for studying expectations**

Research on expectations and consumer confidence has investigated optimism, pessimism, and directional forecasts through linear regression, binary and multinomial logistic regression, and ordered choice models (Kumar et al., 2017; Coibion et al., 2023). These methods facilitate hypothesis testing and the assessment of marginal effects; however, they assume linearity and additivity, prioritizing statistical significance over predictive efficacy (Baghestani et al., 2023; Kumar et al., 2017). Ordered probit and logit models are frequently employed for qualitative data such as inflation and income expectations; however, they are inadequate in capturing intricate interactions and non-monotonic relationships among household characteristics, perceptions, and macroeconomic conditions (Coibion et al., 2023; Kumar et al., 2017). Numerous studies on expectations primarily emphasize sentiment correlates rather than classification accuracy or out-of-sample forecasting quality (Baghestani et al., 2023; Kumar et al., 2017).

**2.2.2. Forecasting economic mood with machine learning**

Neural networks, tree-based models, and hybrid econometric-machine learning frameworks are employed for economic sentiment analysis and forecasting (Baghestani et al., 2023; Baratsas, 2024). Non-linear models utilizing neural networks, ensemble methods, and high-dimensional feature selection can more effectively predict sentiment indices, recession probabilities, and asset returns compared to traditional econometric benchmarks (Baratsas et al., 2024; Tehranian, 2023). The integration of survey-derived sentiment metrics with text-based news indicators and macroeconomic time series enhances forecasting efficacy, demonstrating that machine learning models can effectively manage complex nonlinearities and interactions (Baghestani et al., 2023; Baratsas, 2024). The integration of machine learning with conventional causal-inference frameworks in household expectation research is infrequent, leading to challenges in interpretability and causal mechanisms (Chakraborty & Chaudhuri, 2024; Tehranian, 2023).

**2.2.3. Synthesis and research gap**

A forward-looking mindset is a strong predictor of consumption and macroeconomic cycles; nevertheless, socioeconomic research indicates that demographic consequences after subjective assessments are restricted and unstable (Bhandari et al., 2025; Coibion et al., 2023). Employment, income, and cost of living influence optimism and pessimism; yet, linear and ordered models are deficient in non-linearity and predictive capability (BIS, 2025; D'Acunto et al., 2025). Methodological breakthroughs in machine learning improve prediction accuracy but seldom address variable relevance within explanatory and predictive frameworks (Baghestani et al., 2023; Baratsas et al., 2024). This study utilizes Binary Logistic Regression and a Radial Basis Function Neural Network to examine determinants within model categories

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and evaluate the robustness of perception-based factors affecting economic optimism and pessimism in both explanatory and predictive frameworks (Chakraborty & Chaudhuri, 2024; Baratsas et al., 2024).

## 3. Methodology

### 3.1 Data and Variables

This study uses the Rural Consumer Confidence Survey, comprising 7,124 valid data points collected by RBI in March 2025. The dependent variable is future economic optimism, measured as respondents' expectations regarding the general economic condition one year ahead, that is, for 2026, and coded as a binary indicator (1 = optimistic, 0 = pessimistic). Explanatory variables are grouped into two categories. Demographic and socioeconomic traits encompass age groups, sex, educational attainment, household dimensions, quantity of income-generating members, occupational classifications, family income ranges, and agricultural land revenue in Table 1. These variables are operationalised by dummy indicators accompanied by suitable reference categories.
Subjective economic perceptions capture respondents' assessments of changes over the previous year in general economic conditions, employment conditions, household income, household spending (total, essential, and non-essential), general prices, and inflation. Perception variables are measured on a three-point Likert scale reflecting deterioration, no change, or improvement, and are treated as ordered predictors. This distinction between objective characteristics and subjective assessments underpins the empirical strategy.

Table 1. Descriptive statistics of demographic, socioeconomic, and subjective perception variables.

| Variable | Description | Measurement / Coding | Category / Value | Count | Percentage (%) |
|---|---|---|---|---|---|
| **Economic Outlook (1 year ahead)** | Outlook on the general economic condition | Nominal (Binary) | Optimistic (1) | 5,378 | 60.0 |
| | | | Pessimistic (0) | 2,100 | 23.4 |
| **Age 30–39** | Respondent aged 30–39 | Nominal (Dummy) | Yes (1) | 2,400 | 26.8 |
| **Age 40–59** | Respondent aged 40–59 | Nominal (Dummy) | Yes (1) | 2,993 | 33.4 |
| **Age ≥60** | Respondent aged 60+ | Nominal (Dummy) | Yes (1) | 1,082 | 12.1 |
| **Male** | Gender of respondent | Nominal (Dummy) | Yes (1) | 5,212 | 58.1 |
| **Income ₹5k–<₹10k** | Monthly household income | Nominal (Dummy) | Yes (1) | 2,958 | 33.0 |
| **Income ₹10k–<₹25k** | Monthly household income | Nominal (Dummy) | Yes (1) | 3,569 | 39.8 |
| **Income ₹25k–<₹50k** | Monthly household income | Nominal (Dummy) | Yes (1) | 1,114 | 12.4 |
| **Income ≥₹50k** | Monthly household income | Nominal (Dummy) | Yes (1) | 449 | 5.0 |
| **Education** | Educational attainment | Nominal | Yes (1) | 549 | 6.1 |

| | | | | | |
|---|---|---|---|---|---|
| **below 5th** | | (Dummy) | | | |
| **Education 5th–10th** | Educational attainment | Nominal (Dummy) | Yes (1) | 2,568 | 28.6 |
| **Education 10th–<12th** | Educational attainment | Nominal (Dummy) | Yes (1) | 1,640 | 18.3 |
| **Education 12th** | Educational attainment | Nominal (Dummy) | Yes (1) | 1,646 | 18.4 |
| **Graduate** | Educational attainment | Nominal (Dummy) | Yes (1) | 1,593 | 17.8 |
| **Post-graduate** | Educational attainment | Nominal (Dummy) | Yes (1) | 425 | 4.7 |
| **Household size 2–4** | Number of family members | Nominal (Dummy) | Yes (1) | 3,522 | 39.3 |
| **Household size ≥5** | Number of family members | Nominal (Dummy) | Yes (1) | 4,859 | 54.2 |
| **Agricultural land income** | Income-generating agricultural land | Nominal (Dummy) | Yes (1) | 2,871 | 32.0 |
| | | | | | |
| **Variable** | **Description** | **Measurement / Coding** | **Category / Value** | **Count** | **Percentage (%)** |
| **Perception: General Economic Condition** | Perceived change in overall economic condition compared to one year ago | Ordinal (1–3) | Worsened (1) | 3,114 | 34.7 |
| | | | Remained the same (2) | 2,137 | 23.8 |
| | | | Improved (3) | 3,713 | 41.4 |
| **Perception: Employment Scenario** | Perceived change in employment conditions compared to one year ago | Ordinal (1–3) | Worsened (1) | 3,176 | 35.4 |
| | | | Remained the same (2) | 2,236 | 24.9 |
| | | | Improved (3) | 3,552 | 39.6 |
| **Perception: Household Income** | Perceived change in household income compared to one year ago | Ordinal (1–3) | Worsened (1) | 2,682 | 29.9 |
| | | | Remained the same (2) | 4,064 | 45.3 |
| | | | Improved (3) | 2,218 | 24.7 |
| **Perception:** | Perceived change in | Ordinal (1–3) | Decreased | 201 | 2.2 |

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| | | | | | |
|---|---|---|---|---|---|
| **Household Spending** | total household spending compared to one year ago | | (1) | | |
| | | | Remained the same (2) | 657 | 7.3 |
| | | | Increased (3) | 8,106 | 90.4 |
| **Perception: Essential Spending** | Perceived change in essential spending compared to one year ago | Ordinal (1–3) | Decreased (1) | 198 | 2.2 |
| | | | Remained the same (2) | 717 | 8.0 |
| | | | Increased (3) | 8,049 | 89.8 |
| **Perception: Non-Essential Spending** | Perceived change in non-essential spending compared to one year ago | Ordinal (1–3) | Decreased (1) | 2,016 | 22.5 |
| | | | Remained the same (2) | 1,711 | 19.1 |
| | | | Increased (3) | 5,237 | 58.4 |
| **Perception: General Prices** | Perceived change in general prices compared to one year ago | Ordinal (1–3) | Decreased (1) | 8,525 | 95.1 |
| | | | Remained the same (2) | 308 | 3.4 |
| | | | Increased (3) | 131 | 1.5 |
| **Perception: Inflation** | Perceived inflation compared to the previous year | Ordinal (1–3) | Increased less than last year (1) | 6,675 | 74.5 |
| | | | Increased similar to last year (2) | 1,483 | 16.5 |
| | | | Increased more than last year (3) | 367 | 4.1 |

Source: Author's Work

### 3.2 Binary Logistic Regression (BLR)

A binary logistic regression (BLR) framework is used to find the factors that will affect future economic optimism and to test H1 and H2. The model calculates the likelihood of optimism based on the explanatory variables. A hierarchical specification is adopted. The baseline model includes only demographic and socioeconomic variables, establishing their standalone explanatory power. Next, subjective economic perception variables are included to make the extended model. This lets us directly measure how much they add to the model. We use likelihood ratio tests, pseudo $R^2$ measures (Cox–Snell and Nagelkerke), classification accuracy, and the Hosmer–Lemeshow goodness-of-fit test to see how well the model works. Results are reported as odds ratios to facilitate interpretation.

### 3.3 Radial Basis Function (RBF) Neural Network

To assess robustness and address H3, a Radial Basis Function (RBF) neural network is employed as a supplementary machine learning approach. The model possesses identical predictors to the extended BLR specification. Prior to estimate, continuous covariates are standardised. The dataset is randomly divided into training (70%) and testing (30%) samples to facilitate out-of-sample validation. The selection of the network architecture, including the quantity of hidden units, is determined by its predictive accuracy on the test sample. Classification accuracy assesses a model's performance, whereas normalised variable importance scores identify the most significant predictors.

### 3.4 BLR versus RBF Comparison

Employing both BLR and RBF models concurrently facilitates a comparison between parametric econometric inference and nonparametric machine learning prediction. BLR provides explicit estimates of effects and evaluates hypotheses, whereas RBF accommodates nonlinearities and intricate interactions in Figure 1. When both methodologies concur on the primary predictors, the outcomes are more dependable. If they dissent, it may indicate that the econometric model fails to sufficiently account for nonlinear factors.

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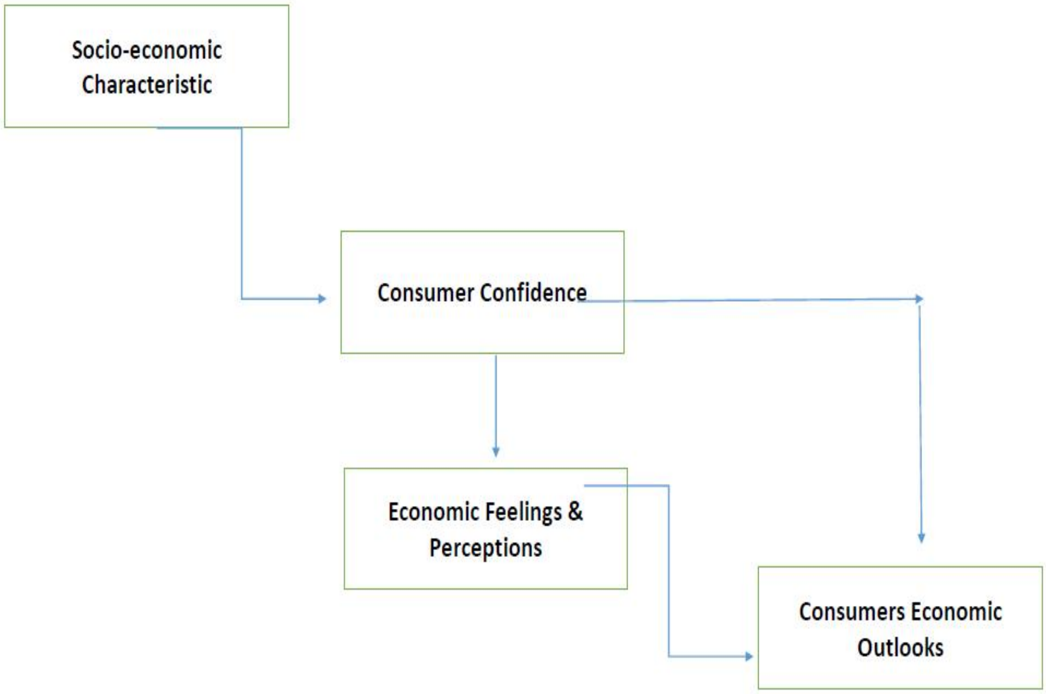


**Figure 1.** Conceptual Framework on Consumer Economic Outlooks
Source: Author's Work

## 4. Results

### 4.1 Descriptive Statistics

Table 1 delineates the descriptive profile of the study sample (N = 8,964), from which 7,124 observations were preserved for multivariate analysis following the exclusion of missing data. Approximately 60.0% of respondents indicated optimism on economic prospects one year hence, while 23.4% conveyed pessimism, reflecting a generally favourable perspective. The sample exhibits socioeconomic diversity, with the predominant age group being 40–59 years (33.4%), followed by 30–39 years (26.8%). Male participants represent 58.1% of the sample. The income distribution is biased towards lower- and middle-income brackets, with over 73% of households earning less than ₹25,000 monthly. Educational attainment is diverse, with 64.6% of respondents possessing education ranging from 5th grade to graduation. Subjective economic perspectives exhibit significant variability. Significantly, 41.4% observed an enhancement in overall economic conditions compared to the prior year, while 39.6% indicated better employment conditions. Conversely, perceptions of prices and inflation exhibit significant asymmetry, with 95.1% reporting a decline in general prices and 74.5% claiming that inflation rose less than in the preceding year.

### 4.2. Explanatory Power of Subjective Economic Perceptions

To evaluate whether subjective economic perceptions provide greater explanatory power for future economic optimism than demographic and socioeconomic characteristics, a binary logistic regression was employed.

#### 4.2.1 Baseline Model: Demographic and Socioeconomic Variables

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Model 1 comprises solely demographic, income, educational, family structure, occupational, and agricultural income variables. The model demonstrates statistical significance ($\chi^2 = 139.59$, $p < 0.001$), although possesses restricted explanatory capacity, indicated by a Nagelkerke $R^2$ of 0.028. The categorisation accuracy is 71.5%, predominantly influenced by the accurate classification of optimistic responders in Table 2. Numerous socioeconomic variables are statistically significant, such as income categories and age cohorts; yet, their marginal effects are minimal. For example, respondents with earnings of ≥₹1 lakh have increased odds of optimism (OR = 2.35, $p < 0.01$), whereas older age cohorts indicate diminished odds compared to the reference category.

Table 2. Logistic regression results – demographic and socioeconomic variables only (Model 1)

| Variable | Coefficient (B) | Std. Error | Odds Ratio | p-value |
|---|---|---|---|---|
| Age 30–39 | −0.158 | 0.078 | 0.854 | 0.045 ** |
| Age 40–59 | −0.291 | 0.078 | 0.748 | 0.000 *** |
| Age ≥60 | −0.418 | 0.108 | 0.658 | 0.000 *** |
| Male | −0.223 | 0.081 | 0.800 | 0.006 *** |
| Income ₹5k–<₹10k | 0.219 | 0.092 | 1.244 | 0.018 ** |
| Income ₹10k–<₹25k | 0.405 | 0.093 | 1.500 | 0.000 *** |
| Income ₹25k–<₹50k | 0.619 | 0.120 | 1.857 | 0.000 *** |
| Income ₹50k–<₹1L | 0.667 | 0.178 | 1.948 | 0.000 *** |
| Income ≥₹1L | 0.856 | 0.289 | 2.353 | 0.003 *** |
| Unemployed / Student / Others | 0.215 | 0.103 | 1.240 | 0.037 ** |
| Income from agricultural land | 0.183 | 0.060 | 1.201 | 0.002 *** |
| Constant | 0.778 | 0.180 | 2.177 | 0.000 *** |

Source: Author's Work

### 4.2.2 Extended Model: Inclusion of Subjective Economic Perceptions

Model 2 enhances the baseline specification by including subjective assessments of economic conditions, employment, income, expenditure, and inflation. The incorporation of these variables leads to a significant enhancement in model fit. The omnibus test is statistically significant ($\chi^2 = 2619.50$, $p < 0.001$), and the Nagelkerke $R^2$ rises markedly to 0.441, indicating over a 15-fold enhancement in explained variance compared to Model 1. The predictive performance significantly enhances, with total classification accuracy increasing to 81.1%, and the correct classification of pessimistic respondents going from 0% to 64.3%. The Hosmer–Lemeshow test is negligible ($p = 0.530$), indicating effective model calibration in Table 3.

Table 3. Logistic regression results with subjective economic perceptions included (Model 2)

| Variable | Coefficient (B) | Std. Error | Odds Ratio | p-value |
|---|---|---|---|---|
| **Age ≥60** | −0.317 | 0.135 | 0.728 | 0.019 ** |
| **Male** | −0.281 | 0.098 | 0.755 | 0.004 *** |
| **Household size ≥5** | 0.279 | 0.140 | 1.322 | 0.046 ** |
| **Education: Post-graduate** | −0.510 | 0.208 | 0.601 | 0.014 ** |
| **Perception: General economic condition** | 1.272 | 0.044 | 3.567 | 0.000* |
| **Perception: Employment condition** | 0.708 | 0.042 | 2.031 | 0.000* |
| **Perception: Household income** | 0.177 | 0.048 | 1.194 | 0.000 |

| | | | | |
|---|---|---|---|---|
| | | | | *** |
| **Perception: Inflation** | 0.321 | 0.068 | 1.378 | 0.000 *** |
| **Constant** | −2.914 | 0.374 | 0.054 | 0.000 *** |

Source: Author's Work

Table 4. Comparison of Logistic regression results with and without subjective economic perceptions.

| **Model Diagnostic** | **Model 1: Demographic & Socioeconomic Variables** | **Model 2: + Subjective Economic Perceptions** |
|---|---|---|
| **Observations** | 7,124 | 7,124 |
| **Nagelkerke $R^2$** | 0.028 | 0.441 |
| **$\chi^2$ (df)** | 139.59 (25) *** | 2619.50 (32)* |
| **Hosmer–Lemeshow p-value** | 0.884 | 0.530 |
| **Classification accuracy (%)** | 71.5 | 81.1 |
| **Improvement over Model 1** | — | Substantial |

Source: Author's Work
*Notes:*
**** denotes significance at the 1% level.*
*Both models satisfy goodness-of-fit criteria based on the Hosmer–Lemeshow test.*
*The sharp increase in Nagelkerke $R^2$ and classification accuracy in Model 2 indicates the substantial explanatory contribution of subjective economic perceptions.*
Models incorporating subjective economic perceptions explain significantly more variation in future economic optimism than models relying solely on demographic and socioeconomic characteristics, which is aligned to our hypotheses in Table 4.

### 4.3 Relative Influence of Subjective Economic Perceptions

Using odds ratios derived from Model 2, an evaluation is carried out to determine the relative significance of various subjective judgements. Based on the findings, it is evident that views of employment and overall economic conditions are more influential than any other subjective variables. The odds of future optimism are increased by a factor of 3.57 (OR = 3.567, $p < 0.001$) upon a one-unit improvement in perceived overall economic conditions. This makes it the single most influential predictor, as it affects the likelihood of future optimism. A considerable beneficial effect is also exerted by perceived improvements in employment conditions, with an odds ratio of 2.03 and a p-value of less than 0.001. The perceptions of household income, on the other hand, have a somewhat minor impact (odds ratio = 1.19, $p < 0.001$), whilst the perceptions about household and essential spending are statistically negligible. Although perceived inflation continues to be substantial, it is secondary in importance (odds ratio = 1.38, $p < 0.001$). This suggests that inflation expectations are significant, albeit they are not as significant as employment and macroeconomic sentiment.

Table 5. Odds ratios and significance of subjective economic perceptions.

| **Subjective perception** | **Odds Ratio** | **p-value** | **Interpretation** |
|---|---|---|---|
| **General economic condition** | 3.567 | 0.000 *** | Strongest driver of optimism |
| **Employment condition** | 2.031 | 0.000 *** | Major positive influence |

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|---|---|---|---|
| **Household income** | 1.194 | 0.000 *** | Moderate influence |
| **Inflation** | 1.378 | 0.000 *** | Secondary macro signal |
| **Household spending** | 0.921 | 0.540 | Not significant |
| **Essential spending** | 0.936 | 0.594 | Not significant |
| **Non-essential spending** | 0.990 | 0.809 | Not significant |

Source: Author's Work

Perceptions of employment conditions exert a more significant positive influence on future economic optimism than perceptions of household income, expenditure, or prices, which is also aligned to our hypotheses.

### 4.4. Convergence Between Econometric and Machine Learning Approaches

To assess whether econometric and machine learning techniques yield consistent identification of the primary determinants of economic optimism, the findings from the logistic regression are contrasted with those obtained from the Radial Basis Function (RBF) neural network. The RBF model exhibits consistent predictive performance, achieving a classification accuracy of 71.1% on the training dataset and 72.8% on the testing dataset. The area under the ROC curve is 0.634, reflecting moderate discriminatory capability in Table 6. Variable importance analysis indicates that subjective economic perceptions remain predominant, especially those concerning household expenditure and essential spending, with perceptions of income and employment following closely behind. Importantly, perceptions of the overall economy and employment continue to be among the most significant predictors, aligning with the results of the logistic regression analysis. Demographic variables, although included, demonstrate markedly reduced normalised importance.

**Insert Table 5 here**

Table 6. RBF neural network variable importance rankings

| Variable | Normalized Importance (%) | Rank |
|---|---|---|
| **Perception: Household spending** | 100.0 | 1 |
| **Perception: Essential spending** | 99.4 | 2 |
| **Age ≥60** | 72.7 | 3 |
| **Income ₹5k–<₹10k** | 59.4 | 4 |
| **Perception: Household income** | 54.3 | 5 |
| **Income ₹10k–<₹25k** | 49.6 | 6 |
| **Education 5th–10th** | 39.4 | 7 |
| **Household size ≥5** | 35.1 | 8 |
| **Education: Graduate** | 29.4 | 9 |
| **Perception: General economic condition** | 26.2 | 10 |
| **Perception: Inflation** | 22.4 | 11 |
| **Education: 12th** | 21.7 | 12 |

Source: Author's Work

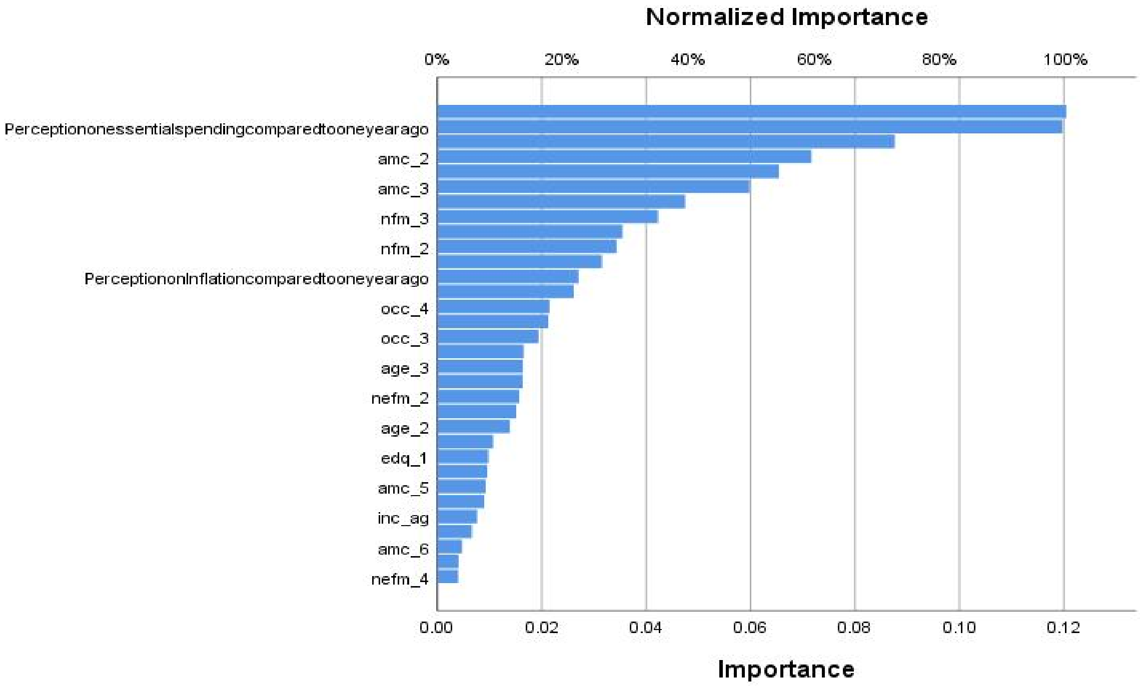


Figure 2. Independent variable importance plot from RBF neural network.

Source: Author's Work

These results demonstrate strong methodological convergence, with both approaches consistently identifying general economic sentiment and employment perceptions as the primary drivers of future economic optimism, the result is in line with our hypotheses in Figure 2.

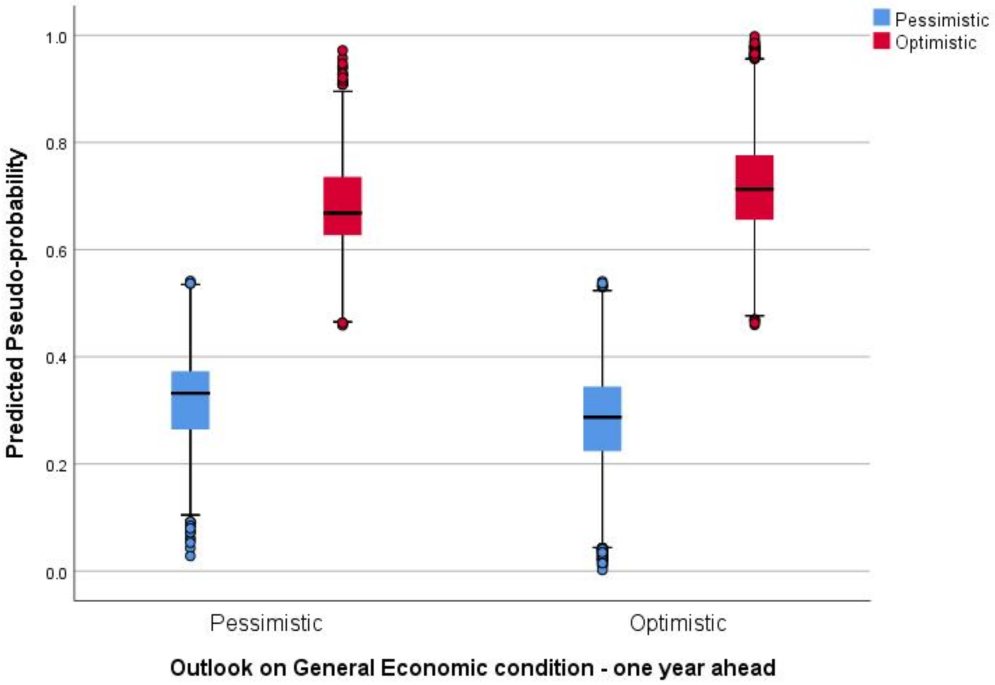


Figure 3: Predicted Pseudo-probability for Outlook on General Economic Condition -One Year Ahead.

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Source: Author's Work

The model clearly identifies distinct categories for economic outlook predictions, as can be seen from Figure 3. above. Predicted pseudo-probabilities are stratified by respondents' economic outlooks. The predicted probabilities for optimistic respondents are significantly higher than those of pessimistic respondents. While optimistic respondents yield median predicted probabilities between 0.65 and 0.75, pessimistic respondents yield median predicted probabilities between 0.25 and 0.35. There is very little overlap between the interquartile ranges of the two groups, indicating that the model systematically assigns very high probabilities of optimistic outcomes and is therefore highly predictive of actual outcomes.

## 5. Discussion

The results indicate clear and strong evidence that individual subjective economic perceptions are the primary basis for developing optimism about the economy going forward, significantly greater than the influence of traditional demographics and socioeconomic backgrounds as perceived by individuals. With specific reference to RQ1 and H1, the increase in variance explained from a Nagelkerke $R^2$ of 0.028 in a model based solely on demographics to an increase to $R^2 = 0.441$ with the addition of individual subjective economic perceptions supports that individuals' expectations regarding the future economy will be fundamentally based on their subjective assessment instead of objective economic indicators. This finding is consistent with current theories regarding the way individuals form expectations based on their past experiences and the narratives of those around them based on those experiences, particularly during periods of uncertainty (Bordalo et al., 2018; Coibion et al., 2020). In relation to RQ2 and H2, general economic conditions and employment prospects are by far the strongest and most consistent predictors of economic optimism and are more significant than household income, consumption, or price-related perceptions. The importance of employment perceptions as a strong predictor is both consistent with and supported by recent empirical research that has demonstrated that individuals assess broad economic trajectory based on their perceptions of the labor market, particularly in developing or emerging economies where the volatility of the labor market has a direct impact on household security (Das et al., 2021; Kumar & Sahu, 2023). While the current study provides evidence of the existence of a causal relationship between inflation expectations and consumer confidence based on both quantitative (via logistic regression analysis) and qualitative (via qualitative regression analysis) methods, our work further supports previous research that supports this conclusion through a different methodological approach. Our findings support previous research by Athey & Imbens (2019) and Mullainathan & Spies (2017), which support the complementary application of econometric and machine learning to the validation of behavioural macroeconomic relationships. Our analyses demonstrate that consumer confidence is not solely a function of an individual's current employment or income status; rather, it is a function of macroeconomic conditions. This provides valuable new information regarding how to develop and implement effective consumer confidence-building strategies and how to communicate effectively with consumers in developing and implementing effective consumer expectations management strategies.

## 6. Conclusion, Implications, and Directions for Future Research

### 6.1. Conclusion

Findings indicate that a primary determinant of household economic optimism is the way in which households perceive the labour market and broader macro-economic conditions. Household or individual perceptions of the housing market (the amount of money they will pay), consumers for their goods/services (the number of consumers), and the price of their goods/services (the price they expect to receive) are less predictive and exhibit lower effect sizes on future household economic optimism than other perceived economic variables (perceptions of macroeconomic conditions/labour market conditions). Perception-based explanatory variables have a greater degree of predictability than other explanatory factors, as evidenced by the fact that in both methodologies, Binary Logistic Regression and Radial Basis Function, the construction of the models, based on perception-based explanatory variables, had greater than tenfold explanatory power over other factors, thus dramatically increasing the predictive accuracy of the models. Additionally, both methods produced similar results with respect to the relationships between perception-based explanatory variables, macroeconomic variables, labour market variables, and household economic optimism. The results of both methods suggest that household or individual perception of macroeconomic conditions/labour market conditions is significantly related to household economic optimism, and highlight the need to consider expectations with respect to policy or economic behaviour.

### 6.2. Implications

The findings carry several important implications for research, policy, and economic modelling. *First,* results highlight that subjective views might hold more weight than objective economic aspects in macroeconomic theory, particularly when considering both behavioural and expectation-based perspectives. It can be inferred that relying solely on structural characteristics of a household will lead to an underestimation of the role of expectations in determining economic performance. *Second,* policymakers should be aware that the influence that views (particularly those related to labour and the economy) have on outcomes and the efficacy of policies is as important, if not more so, than the objective nature of the information itself. Therefore, Central Banks and Government bodies need to keep a close eye on the narratives related to the employment and economy to develop effective policies and to contribute to stabilising consumer spending and investment. *Third*, the strong concordance between econometric and machine-learning models emphasises the necessity to combine statistical inference with flexible prediction methods. Hybrid methods allow researchers to identify statistically interpretable determinants and complex nonlinear expectation-generating patterns.

### 6.3. Directions for Future Studies

Researchers should conduct future studies using panel data to evaluate the causal pathways through which perceptions change and how they affect economic expectations. Researchers should also disaggregate their analyses by geographic region, industry, and employment type so that they understand how different local labour market conditions impact optimism. By including a combination of objective macroeconomic data with subjective perceptions, researchers will be able to directly test the existence of perception-reality gaps that occur during expectation formation. Applying ensemble machine learning techniques would also be useful for evaluating non-linear effects and interaction patterns between economic optimism and its effect on consumption, saving, and labour supply decisions. This would ultimately provide stronger insights into the relationship between economic optimism and its impact on the economy from a behavioural and policy perspective.

**CRediT Authorship Contribution Statement**

*Ashis Kumar Sa;* Conceptualization, Investigation, Data curation, Formal analysis, Writing original draft. *Jayprakash Rath;* Conceptualization, Writing review & editing, Validation,

Supervision. *Chandra Aditi Kundanlal;* Reconceptualization, investigation, and validation, writing original draft, editing, grammar check, and English check for effective communication.

**Declaration of Generative AI and AI-assisted technologies in the writing process**

While preparing the manuscript, the author used Grammarly and QuillBot to check the spelling, grammar and to choose appropriate words for effective communication of the research findings. And tools like ChatGPT were used only for restructuring tables and table formatting. After using tools, the authors reviewed and edited the content as needed. The authors took full responsibility for the content of the publication.

**Declaration of competing interest**

The authors declare no competing interests that could influence the work reported in this paper.

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**Data Availability Statement**

Data are available on request.

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